A PREDICTIVE ANALYSIS OF CUSTOMER EXPERIENCE OF MOBILE FITNESS APPLICATIONS USING MACHINE LEARNING ALGORITHMS

Synopsis of the Research Proposal

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Abstract:

Regular physical activity is one of the prominent aspects that helps in maintaining an appropriate fitness level. Regular exercising has a significant impact on the physical and mental health of an individual. Rigorously following a specific physical activity is highly important to achieve good health and mental well-being. Most prominently, fitness enthusiasts rely on physical trainers and instructors for maintaining their health. However, the increased risks due to the pandemic and other hygiene related issues has restricted the users to physically access fitness institutions. In such cases, mobile fitness applications help users to gain online access to various instructors and fitness institutions. Several smart applications and fitness trackers are readily available in recent times that promote physical activity. These smart applications monitor the physical activity of each individual and track different fitness parameters on a regular basis. Due to their simple accessibility, flexibility, and excellent user interface, mobile fitness applications are gaining hue popularity. With the integration of artificial intelligence based machine learning techniques, mobile fitness applications are being transformed apparently. This transformation has widened the horizon of these fitness applications and thereby play a prominent role in increasing their application. Although several mobile fitness applications are available, their accuracy is questionable. It cannot be ensured that the recordings of the fitness trackers are accurate and appropriate. In this context, the research related to the design and development of smart fitness applications is still persistent. This research aims to evaluate the experience of different customers using mobile fitness applications. A predictive analytics approach will be adopted to analyze the customer experience about fitness applications. In addition, a hybrid machine learning (ML) algorithm will be implemented for achieving high accuracy of tracking. The performance of the hybrid ML algorithm will be tested and validated using different performance metrics and comparative analysis.

1. Introduction

1.1 Background of the Study

Physical activities such as exercising, walking, or running are essentially important in achieving good fitness and preventing chronic diseases like cardiovascular problems, type 2 diabetes etc and other physiological issues such as depression [1]. Since it occupies a prominent place in improving the health of an individual, the Physical activity guidelines for Americans have suggested that young individuals and adults must adhere themselves to physical activities at least 120 minutes in a week. For individuals with moderate health issues, it is recommended that adults must carry out a rigorous and highly intense physical activity such as aerobics [2]. It is anticipated that nearly 50% of the adults in the United States are physically inactive and approximately three million deaths occurred worldwide due to the physical inactivity [3]. Considering the significance of physical inactivity, it is crucial to develop effective, flexible, reliable, and scalable devices to encourage adults to carry out physical activities. One such potential approach is to employ smartphones for personalizing the physical activities and improving their physical health [4-5]. Smartphones enable effective communication which enables the application of artificial intelligence based techniques and various data driven analytics for developing applications related to physical exercise programs based on the requirement of each individual. In addition, recent smartphone technology has integrated advanced features for tracking physical health conditions [6]. This technology makes it easy for collecting real-time data and health information from each individual.

Smartphones are accompanied with digital technologies such as smart wearable devices which have brought significant change in people's life. These devices motivate and transform the health of adults [7]. Although most of the physical activities are carried out in workout clubs under the supervision of healthcare instructors, it is not feasible for all adults to reach out to fitness centers. This issue is elevated due to the recent pandemic and other critical issues. The application of smartphone based fitness monitoring techniques has increased after the pandemic and most of the individual’s especially young adults have inclined towards the utilization of smartphone or mobile based fitness applications for monitoring their fitness level [8]. Mobile based applications allow users to practice fitness activities at any place and time based on their convenience. Besides, these applications introduce different and novel activities which help the users to associate themselves with health and fitness. Various researchers have extensively discussed the experience and significance of mobile fitness applications and their

role in improving physical fitness. Few research works have also evaluated the technical contributions of such investigations and the impact of age, gender etc are also investigated [9]. As discussed previously, the propagation and spreading of pandemic has increased the risk of disease transmission due to physical interaction between two individuals. This may have an adverse effect on the non-infected individuals and put their lives also at risk. Several measures were taken such as restrictions, lockdown, quarantine and isolation to reduce the physical interaction among the individuals [10]. Due to the fact that people were restricted to access places such as fitness studios, sports clubs, swimming pools, and other public facilities during the pandemic, more people were kept away from their fitness regime. In addition, lack of fitness increased the sedentary lifestyle which also affected the interest of the people to carry out outdoor activities and has restricted them to their indoor environment. This is the main reason for the increased popularity of digital fitness monitoring tools for increasing physical activity during their daily regime [11-12]. In this context, researchers have suggested the adaptation of online fitness centers as the most crucial factors in the healthcare industry in 2021 [13].

Mobile fitness based applications for improving the physical fitness of the individuals has simplified the fitness regime since it allows a flexible routine. However, few existing research works have suggested that the adoption of online fitness activities is not sufficient. And most of the research works have also questioned the accuracy of the online fitness and monitoring applications. Hence few studies have focused on determining the factors affecting the practice of smart fitness applications using advanced technologies. Machine learning (ML) is a branch of artificial intelligence which allows computer based systems to acquire new information and make decisions by learning data. The learning process of ML algorithms are similar to the learning mechanisms of humans [14]. ML techniques automate their tasks and help the users to obtain productive outcomes. In order to obtain better results, ML algorithms have to select relevant variables in an appropriate manner. However, it is highly challenging to accurately select the variables such as timer, activity tracker etc. These variables or parameters play an important role in the fitness applications and hence it is one of the most potential factors.

1.2 Overview of Mobile Fitness Applications

Advanced techniques based on ML are gaining huge popularity since it enhances all applications in almost all industries. As discussed previously, the lockdown and quarantine has affected the lives of several people and majority of the people opted for smart and mobile

fitness applications to be physically active. Numerous research works are available that have accelerated the application of ML algorithms for developing smart mobile fitness applications. Hence, this research emphasizes the application of ML techniques for predicting whether the home workouts using mobile fitness applications are useful or not. In comparison to conventional business intelligence based techniques, ML models allow the fitness companies to gain detailed insights from structured and unstructured data. Besides, ML models are advantageous compared to traditional analytical models in terms of productivity, complexity, reliability, trustworthiness and cost-effectiveness. In practical scenarios, the adaptation of ML based smart applications is cost effective compared to conventional business intelligence and analytical methods. Once ML models are trained to perform a specific task, they are capable of functioning normally without human intervention. This also reduces the vulnerability of applications towards human errors. Also, ML models can be tuned easily using a small amount of manpower. Furthermore, in comparison to conventional analytical methods, ML models can also solve real time problems and gain insights faster in a simplified manner. These advantages have made ML models more popular tools for developing smart fitness applications. Several smartphone applications based on ML for fitness have been proposed in the research works [15-16]. These works have prioritized the utilization of mobile fitness applications and have listed out the persuasive attributes which are required for the fitness enthusiasts to maintain their fitness regime through the continuous utilization of the smart application. The works mentioned in [15-16] have also suggested that there is a lack of required experimental validation which can validate the efficacy of the specific attributes for existing mobile fitness applications. It can be inferred from existing studies that there is a need to monitor the continuous step goals and most of the existing applications are not accurate in recording the step goals. It can also be noted that maintaining user participation and their experience is one of the crucial challenges in developing potentially efficient physical activity monitoring platforms. There is a need to personalize the goals of individuals via fitness apps using intelligent user interfaces. This research intends to address these issues and investigate the role of ML based mobile fitness applications in increasing the physical fitness of the individuals.

2. Literature Review

Advanced and expedient fitness applications is one of the prominent requirements for human beings in day to day life. It is essential to provide appropriate fitness requirements for every individual irrespective of their age, gender, location and health status. Hence adoption of smart or mobile fitness applications has become one of the prominent aspects of modern society. Mobile fitness applications have undergone significant transformation in recent times. The emergence of smart devices based on advanced technologies have enhanced the quality of fitness applications and health monitoring systems. Several research works have been published in recent times that have discussed the adoption of different fitness applications. This section reviews the existing works related to the state of art of mobile fitness applications and discusses their role in improving the physical fitness of individuals.

2.1 Predictive Analysis

A comprehensive predictive analysis about fitness applications and its users is presented in [17]. The main intention of this research is to understand the role of health consciousness among the users. For predictive analysis, the study considers the feedback of certain users to evaluate the fitness applications and create health consciousness among the users. Based on the obtained data, the study predicts the utilization of fitness applications. The results help the health industry to generalize the significance of fitness applications. The work presented in [18] discussed the implementation of predictive analysis in the healthcare sector. The predictive analysis helps in analyzing the historical data to predict future events. The transition of traditional health and fitness applications into predictive analysis is considered as a significant advancement for healthcare organizations from both a technology and business perspective. The authors in [19] discussed the emerging technologies and predictive analytics for understanding the perspective of healthcare systems. The existing frameworks for healthcare and marketing can be understood in terms of three main aspects namely preferences, precision, and processes. The study describes how predictive analytics and other supportive technologies can help in enhancing the adaptability of tech and analytics enabled healthcare. The study presented in [20] implemented a Technology Acceptance Model (TAM) to investigate the role of self-exercising among different mobile fitness application users. The model is used to predict current users' intention and aims to increase the user retention rate.

2.2 Mobile Fitness Application

The authors in [21] discussed the process of physical activity recommendation using mobile fitness applications. The study emphasized the utilization of DL algorithms for estimating the physical activity. In the proposed work, a two-level clustering was performed on the dataset which consists of an individual's physical and physiological attributes along with regular activity patterns. The proposed deep learning model makes use of the user information with a complete feature set. However, to deal with partial features, the proposed model was trained with the information of uses who possess related features. The clusters are classified into different multiple clusters for generating more accurate results. This allows the fitness model to provide a personalized activity recommendation and data-driven information. The personalized activities are recommended based on hourly patterns and activities of the users. The deep learning model is trained using the historical information and current routine. The performance of the proposed approach was evaluated using practical data and was validated by comparing the performance with other existing techniques.

In [22] the authors used step count data and ML algorithms such as logistic regression (LR) and support vector machines (SVM) for predicting the relapsing exercise users based on the information obtained from mobile fitness application. The discontinuation prediction score (DiPS) of the SVM and LR models is computed using the daily step counts. The DiPS score was also used as an early warning score for predicting when the user will relapse from their regular fitness routine. Results show that DiPS exhibited accurate and trustworthy predictions with high precision and recall score. In [23] an ensemble ML algorithm was used to demonstrate the high prediction accuracy of DiPS in smart fitness applications compared to other techniques including SVM and LR models. The study revealed that the wearable and smart activity tracker devices can motivate the users to carry out fitness activities through different platforms [24]. Few factors are associated with the interactions of the individual users. Users also related themselves to controlling features and data management features for analyzing the fitness data and investigating the progress updates on a regular basis. These factors also play an important role in recommending the exercise for the users. It is revealed from the investigation that factors such as social, psychological and behavioral factors act as catalysts to encourage physical activity in young adults [25].

Collecting the data related to active participants with personalized feedback helps in obtaining accurate and precise emotional responses. It was noted that users or individuals with lower

activity levels are more likely to express negative emotional responses but possess a better chance of inclining towards a positive response [26]. Existing research works mentioned in [27-30] focused on employing advanced techniques for increasing the adaptation of wearable smart fitness tracker devices based on the personalized requirements. However, the research related to these devices is still in the infant stage and this constitutes a prominent research gap. It is also important to note that the operation of wearable fitness tracking devices cannot ensure the accuracy [31]. The need for adapting appropriate devices based on the user characteristics and requirements is also discussed in [32] and it can be observed from the study that it is essential to record the user experience in terms of interface, aesthetics and physical device in order to facilitate the device for a longer duration.

2.3 Application of Hybrid Machine Learning

The application of hybrid approaches that integrate learning algorithms such as ML and DL for different applications can be considered as a possible solution to overcome the problems associated with the implementation of single ML and DL models alone. The hybrid methods can adapt itself to new environments and can be trained to ensure better performance efficiency. A novel neural network approach was proposed by (Pang et al., 2020) [33] which uses multi-stock high-dimensional historical data for stock prediction. The approach incorporated LSTM with an embedded layer and an auto encoder for prediction. The embedded deep LSTM showed better results compared to the latter approach. (Chung & Shin, 2020) [34] integrated the CNN model with an evolutionary genetic algorithm (GA) for forecasting the variations in the stock indices. Deep learning (DL) models can be considered as a potential tool to overcome the problems associated with ML models. DL models such as CNN, Recurrent neural networks (RNN) such as LSTM models extract important and relevant features from the collected data and identify suitable data patterns to accurately forecast energy usage in household appliances (Aurangzeb et al., 2022) [35] (Alden et al., 2020) [36]

The existing literary works suggest that the study should discuss the need to adopt the type of device which matches the fitness requirement of an individual. An ample amount of research is available for the utilization of the fitness tracker devices for recording the daily activity of the user. To motivate the users to improve their healthy habits, it is recommended to aggregate user experience and overcome the limitations associated with existing fitness tracking devices. The proposed research work states that a daily fitness regime is highly essential to maintain a

healthy lifestyle. In this context, this research presents a hybrid machine learning approach for predicting and improving the accuracy of personalized fitness tracking devices.

3. Present Study

3.1 Statement of the Problem

Modern technology is rapid enough yet for users to quickly switch between brands, apps, and innovations if one does not meet their needs within the first five minutes of use. This is also a reflection of the increased competition brought on by this rapid pace. Companies who create mobile apps simply cannot afford to fall behind in the fight against constantly advancing technology. Nowadays, practically every mobile application chosen by the user has machine learning built in. For instance, the food delivery app will display the eateries that deliver the cuisine we choose to order, our on-demand taxi applications will display the location of the rides in real-time, and our time management apps will instruct the users on how to prioritize our workload.

Artificial intelligence (AI) and machine learning are becoming more and more prevalent in the twenty-first century. Both are becoming more crucial parts of modern training regimens. AI is now inextricably linked to fitness and health. Technologists claim that AI makes everything better. Fitness has the capacity to empower the app by significantly raising engagement, which could result in long-term income. The apps with AI capabilities can provide users a number of benefits. A fitness enthusiast may benefit financially since, for instance, artificial intelligence fitness trainers are less expensive than human trainers, but joining a gym may be prohibitively expensive or difficult to squeeze into our busy lives. Additionally, AI-driven fitness software might improve the enjoyment and intrigue of an exercise.

The work presented in base paper [28] a machine learning method is suggested for evaluating user activity on a platform for at-home workouts. A home training program called Maintain offers everything you need to be in shape, including yoga, cycling, running, and fitness food advice. Here, the authors tested four supervised learning algorithms: support vector machine, k-nearest neighbor, random forest, and logistic regression using data from the entire training set of 7734 Keep users. An accurate rate of 88% was achieved when classifying 850 test samples using the random forest model. This method can forecast consumers' continued use of the home workout application after installation.

The main factor influencing the outcomes of this investigation was keep certification. A person who has obtained the Keep certification logo and had their identity information confirmed is said to have obtained Keep certification. The findings indicate that, among other things, the

platform still has to be upgraded in terms of genuine identity privacy information. The biggest drawback of random forest is that it can be too extremely slow and inefficient for real-time forecasts when there are a lot of trees. Hence there is a great need for an effective ML technique which can overcome the drawbacks associated with conventional ML classifiers such as RF.

3.2 Significance/ Rationale of the Study

Various research works have discussed various fitness tracking devices based on the user characteristics and requirements. This study indicates the growing demand for the selection of appropriate mobile fitness tracking applications. Despite the availability of different techniques, there is a lack of an effective technique which can address all the limitations to strengthen the operating mechanism of existing techniques. This problem motivates this research to emphasize the application of hybrid ML algorithms for improving the accuracy of mobile fitness applications. In addition, the study also necessitates the application of predictive analytics for understanding the customer experience.

This work indicates the growing demand for the implementation of predictive analytics along with machine learning models for enhancing the prediction accuracy. As inferred from existing literary works, there is a lack of an effective technique which can address the challenges and limitations of conventional machine learning and strengthen the operating mechanism of fitness applications. Accurate analysis of customer experience has a greater role to play in fitness companies and hence there is a great demand for developing a suitable technique. Though machine learning models are advantageous, they suffer from various issues such as computational complexity, inability to handle large scale data etc. In this context, the technological improvements in hybrid ML techniques motivate this research to integrate two ML algorithms for achieving desired outcome. The proposed technique focuses on enhancing the high-speed performance of the ML models with high accuracy and scalability. The significance of this study is that it highlights the importance of hybrid ML algorithms in improving the accuracy of fitness applications.

3.3 Objectives of the Study

The research objectives considered in this study are as follows:

- To predict whether home workouts using mobile fitness applications helps the users to maintain their fitness levels using machine learning and predictive analysis.

- To obtain a detailed insight from structured and unstructured data collected from raw datasets.
- To design a hybrid ML model which is faster, accurate, reliable, flexible to learn automatically, and cost-efficient compared to traditional analytical models.
- To analyze the factors influencing continuous exercise participation using fitness applications.
- To validate the performance of the proposed approach by comparing the results with other existing ML models.

3.4 Research Hypothesis

Alternative hypothesis Ha: If the absolute value of the statistical tests, Mean Square Error (MSE), Root Mean Square Error (RMSE), and accuracy, precision, F1-score values are positive, then the proposed model can predict prospective outcome of fitness application with high prediction accuracy compared to other models.

Ha > 0.05; accept alternative hypothesis and reject null hypothesis, the proposed model has better prediction accuracy.

Null hypothesis H0: If the absolute value of the statistical tests, Mean Square Error (MSE), Root Mean Square Error (RMSE), and accuracy, precision, F1-score values are negative, then the proposed model cannot predict prospective outcome of fitness application with high prediction accuracy compared to other models.

H0 < 0.05; accept null hypothesis, and reject alternative hypothesis.

3.5 Research Questions

RQ 1. Can the proposed model achieve better accuracy compared to other existing methods by incorporating the proposed predictive analytics and hybrid ML models?

RQ 2. How does this research overcome the problem of data dimensionality while implementing deep learning algorithms for customer analysis?

4. Proposed Research Methodology

4.1 Research Design

The purpose of this research is to predict whether home workouts using mobile fitness applications helps the users to maintain their fitness levels using hybrid machine learning models. The proposed research is a mixed research methodology since it will incorporate both quantitative and qualitative data and analyze both together to answer the research question. Since the proposed work focuses on predictive analytics for predicting the utilization of fitness applications based on user experience. It is essential to collect quantitative data from the related database. In addition, this research proposes descriptive analysis to understand the integration of predictive analytics and machine learning which requires a qualitative analysis. Hence a mixed research methodology is suitable for the proposed work.

4.2 Sample/ Participants

The target population in this study will be the adults who are above 18 years of age who use mobile fitness applications for maintaining their health regime. The samples will be selected based on the characteristics of a population and the objective of the research. The size of the sample represents the number of participants or observations. In this research the sample size can be considered as around 385 for conducting surveys and questionnaires and a sample size of around 500-600 can be considered for training the machine learning model.

Sample Size 385 is calculated using sample size calculation technique.

$$\text{Unlimited population: } n = \frac{z^2 \times \hat{p}(1-\hat{p})}{\varepsilon^2}$$

$$\text{Finite population: } n' = \frac{n}{1+\frac{z^2 \times \hat{p}(1-\hat{p})}{\varepsilon^2 N}}$$

With confidence level of 95%, margin error of 5%, population portion of 50% and infinite population size.

4.3 Data collection

The quantitative data for the experimental analysis will be collected by conducting surveys, interviews, and questionnaires for the predictive analysis. The data will be collected based on the user experience, usability, and benefits of the application, interpretability and user interface.

The data will be collected from available datasets to train the machine learning model and the real-time data will be collected from the GitHub. The data for the experimental analysis will be collected from different resources like kaggle, github, Consumer Data Research Center (CDRC) and IQVIA repository. The data will be collected from available datasets to train the machine learning model. A novel dataset will be prepared by conducting surveys, interviews, and questionnaires for the predictive analysis. The link for the dataset is given below:

https://www.kaggle.com/datasets/arashnic/fitbit

https://data.cdrc.ac.uk/dataset/fuell-activity-data

https://www.iqvia.com/search#q=data%20sets

https://github.com/topics/garmin-data

This research will use a convenience sampling method. Convenience sampling method is a non-probability sampling used to collect market research data from the available customers or respondents. This sampling method is selected since it provides simple and easy access to the respondents/customers, and is economical and faster.

4.5 Data Analysis

This research employs an exploratory analysis to explore and analyze the data. The exploratory data analysis helps in identifying the relationship between the data and the variables. Here variables are the parameters of ML models such as weights of the neural network, function values, input variables etc. The exploratory analysis also helps in generating hypotheses and solutions for specific problems. After analysis, the data is preprocessed to filter irrelevant data from the input data.

4.6 Overview of the proposed technique

This research aims to implement a Hybrid machine learning algorithm and predictive analysis for achieving high prediction accuracy. The main objective behind selecting a hybrid machine learning approach is its ability to achieve a higher accuracy compared to a single ML algorithm. In addition, hybrid algorithms can handle large scale complex data with high dimensional features also, hybrid ML algorithms can handle computational complexities.

In this research, the predictive analytics model will be developed using a clustering algorithm, classification and prediction model. The clustering algorithm helps in aggregating the data

based on the user's interests and the classification model helps in customer retention by classifying the data and helps in prediction tasks. This simplifies the application and thereby helps the user to prioritize their usage.

The hybrid model will be developed by integrating a K-means clustering (KCM) algorithm for clustering and Bi-directional Long short term memory (Bi-LSTM) as classification and prediction model. K-means is a clustering algorithm that clusters the sample space into k clusters. K-Means clustering algorithm intends to cluster 'n' number of objects into 'k' number of clusters where each object belongs to the cluster with the nearest mean. The K-means algorithm attempts to find an optimal solution by reducing the squared error. On the other hand, LSTM is a type of recurrent neural network which is widely used in data prediction and data classification. Bidirectional LSTM is an advanced version of conventional LSTMs which operates in both directions i.e., forward and backward unlike single LSTM models. Bidirectional LSTM improves the performance of the system architecture with respect to sequence classification issues where all the time steps of the input sequence are accessible. It can train two LSTMs instead of one LSTM on the input sequence.

4.7 Performance Evaluation:

The performance of the proposed approach will be evaluated using different performance metrics such as Accuracy, Mean Absolute Percentage Error (MAPE), Relative Root Mean Square Error (RMSE), and Mean Squared Error (MSE). Also, the performance of the proposed approach will be validated by comparing it with other existing deep learning techniques such as ARIMA, Random Forest (RF), Single LSTM model, XGboost, and Decision Tree algorithms.

MAPE: The mean absolute percentage error (MAPE) will be used for measuring the error in the predicted output. The MAPE is calculated using the below given expression

$$\text{MAPE} = \frac{1}{n}\sum\left(\frac{|Actual - Forecast|}{|Actual|}\right) \quad .....(1)$$

Mean square error (MSE): MSE is an evaluation metric which defines the performance function of the proposed model. MSE measures network performance based on the average error of the forecasting error. The MSE function is used in prediction analysis to verify the results of the experimental analysis. MSE is calculated as shown in equation 2.

$$MSE = \frac{1}{n}\sum_{t=1}^{n} {e_t}^2 \quad \ldots(2)$$

Root mean square error (RMSE): RMSE is one of the commonly used evaluation metrics in predictive and regression analysis. It is equal to the square root of the MSE. This error measurement can tell how the concentration of data is around the most suitable line. Fundamentally, the best value of RMSE is close to zero. The expression for calculating RMSE is given in equation 3.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} {e_t}^2} \quad \ldots.(3)$$

Accuracy: Accuracy is basically determined using MAPE as shown in equation 4:

$$ACCURACY = \left(1 - \frac{1}{n}\sum_{t=1}^{n} \left|\frac{e_t}{y_t}\right| \times 100\right) \times 100 \quad \ldots. (4)$$

Accuracy: Accuracy is basically determined using MAPE as shown in equation 4:

$$Accuracy = (1 - \frac{1}{n} \sum_{t=1}^{n} |\frac{e_t}{y_t}| \times 100) \times 100 \quad \ldots. (4)$$

Recall: Recall for a function is determined as the ratio of the correctly identified samples that are accurately classified and is given as:

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}} \ldots\ldots (5)$$

F1 score is used for measuring the accuracy of the system which can possess the values between 1 and 0. Where 1 represents the best value and 0 represents the worst value. Correspondingly, F1 score is defined as:

$$\boldsymbol{F1\ score} = \frac{\boldsymbol{2 * Precision * Recall}}{\boldsymbol{Precision + Recall}} \ldots. (6)$$

Precision is one of the important performance metrics which determines the performance of the ML classifiers. Precision is defined as the number of accurate positive predictions. It is defined as:

$$\textbf{\textit{Precision}} = \frac{TP}{TP + FP} \ldots. (7)$$

5. Limitations of the study:

The prominent limitations of this study are as follows:

- The study does not focus on generating personalized recommendations of fitness tasks based on the user's interests.
- The privacy and security of user's confidential information such as personal details and financial details are not emphasized in this study.

6. Timeline and Activity Plan

Table 1. Time scheduling of research

Task	Details	Duration
Planning and course of work	The details of the execution will be planned and the course of work will be outlined	1 year
Data collection and Literature Review	The details about experimentation will be collected. Different datasets will be evaluated and the data will be collected from the fitness application datasets. Existing research works will be reviewed and the challenges and research gaps will be identified.	3 months
Design of methodology	The collected data will be validated after checking with the supervisor and after validation, the machine learning techniques will be reviewed in detail and supporting information will be aggregated. A brief outline of the proposed methodology will be designed.	3 months
Implementation	The implementation stage will involve the data collection from the database, preparation of questionnaire, and analyze the data using data analysis methods. The DCNN-GRU model will be executed based on the collected data and the proposed design approach.	6 months
Experimentation and validation of proposed methodology	The experimentation will be conducted in two cycles namely training and testing wherein the results for both training and testing cycles will be evaluated. This stage also involves comparative	3 months

	analysis and validation of the results	
Final compilation and submission of research work/thesis	The results will be demonstrated to the supervisor and once the results are approved, the proposed experimentation will be finalized. Further, the research work will be modified based on the supervisor's comments. Finally the research works will be submitted.	3 months

7. Expected Outcome

The study proposes a novel machine learning and predictive analytics based approach for evaluating the effectiveness of mobile fitness applications. The proposed approach is a hybrid approach which combines a DCNN algorithm and GRU for evaluating the efficacy of the fitness applications. The proposed predictive approach will be designed to attain high prediction accuracy and thereby helps the users to maintain their fitness levels. It is expected that the proposed hybrid ML model will achieve superior performance in terms of different performance metrics namely MAPE, MSE, and RMSE. It is expected that the proposed approach will analyze the factors influencing continuous exercise participation using fitness applications. With the use of a computationally intelligent algorithm, the proposed approach is expected to be an efficient system with high execution time and accompanied with less number of resources. The proposed approach is also expected to handle data dimensionality issues and improve the scalability, and reliability of the proposed approach.

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